ASSESSMENT OF UNCERTAINTY IN AEROSPACE PROPULSION SYSTEM DESIGN AND SIMULATION

D.N. Mavris and B.A. Roth
Georgia Institute of Technology
Atlanta, GA 30332-0150

ABSTRACT

The subject of uncertainty analysis in complex systems design is a broad and bourgeoning field of study. This paper focuses on only three very specific areas of current propulsion research wherein uncertainty plays a pivotal role in the problem formulation. The first is probabilistic approaches to matching engine cycle models to test data. Engine cycle models must have a high confidence of representing the actual engine performance accurately. These models must be matched in the presence of measurement, manufacturing, and other sources of uncertainty. Moreover, the optimal model match tends to change with time such that the problem is stochastic in nature. Current efforts are focusing on using Bayesian statistics to enable a comprehensive (stochastic) treatment of the problem. The second research area of interest is probabilistic analysis methods for estimation of part life in life-limited gas turbine engines. There are many sources of uncertainty in estimating part life, including material properties, material cleanliness/flaw size, part loads, and usage profile. Moreover, life limited parts are subject to accumulated damage over time, and the damage accumulation rate is a strong function of vehicle mission profile and usage. Current efforts are therefore aimed at linking detailed part analysis (finite element and materials models) with higher-level system and mission-level parameters to enable rapid and accurate analysis with the least possible effort. Finally, the role of uncertainty in engine materials selection and insertion is discussed. The materials development process for critical turbine engine parts is very lengthy and subject to considerable uncertainty with regards to the optimal balance of materials properties required for a given application. This is an area of research that will benefit from the development of materials selection methods designed to yield robust materials applicable to the greatest possible number of engines.

INTRODUCTION

A great deal of research activity has occurred in the past decade devoted to probabilistic design methods, driven largely by the need to reduce risk through quantification of uncertainty. This probabilistic design trend is applicable to virtually all complex systems wherein the capital cost of design, manufacture, and operation is high. Aircraft gas turbine engines are a prime example of such complex, capital-intensive systems for which quantification of uncertainty through probabilistic methods is desirable and is also a cost-effective exercise. Gas turbines therefore make a good case study for examining the state-of-the-art in uncertainty analysis. This paper seeks to build upon and update previous work[1] published on this topic.

The objective of this paper is to describe the uncertainty analysis needs for three specific areas within the aircraft gas turbine arena. Uncertainty is a key element in each of the three problems and analysis of uncertainty through probabilistic methods is an integral part of the solution. Particular emphasis is placed on articulating the salient elements of each problem as well as solution approaches currently being pursued. As a disclaimer, we should point out that the examples in paper focus primarily on work with which the authors are involved or intimately familiar. The work presented herein is therefore as a microcosm of the larger body of work presently going on in these fields and is undoubtedly biased based on our past experiences and views. This is in no way intended to be a survey paper of the broader field, but merely a snapshot of a few projects wherein uncertainty plays a pivotal role in the analysis process.

MATCHING (NOISY) ENGINE TEST DATA TO MODEL PREDICTIONS

Creation of computer cycle model representations for engine performance is one of the most basic activities an engine manufacturer must undertake. These high-accuracy cycle models are referred to as "status decks." It is imperative that the status deck results match the actual engine performance with the highest possible precision. For instance, status deck results are used for estimation of overall aircraft performance such that safe operating limits can be estimated. In addition, engine status decks are used for other purposes such as quoting performance guarantees to prospective customers. It is typically the engine manufacturer's responsibility to create these status decks. A poor match of model to actual machine performance can potentially cost the engine manufacturer millions of dollars if it leads to failure to meet performance guarantees to the customer.

The basic status matching problem consists of modifying a set of model parameters (denoted herein as the "X's") so as to make status deck predictions match test data over the entire range of operating conditions. The test data available for use in the matching process may range from a few parameters to many thousands. Moreover, the number of operating points tested may range from a single condition to many thousands of conditions. A typical commercial aircraft engine has a dozen or so X's that are available to be adjusted to find the best match. The objective is to find the set of parameter settings that produces an optimal match while simultaneously accounting for manufacturing and measurement uncertainty inherent in the matching data as well as migration of the nominal design point over time (stochastics of the problem).[2]

There are several criteria that an acceptable status matching method must meet. First, the process must be repeatable with a sound mathematical basis. If different technicians are given the same data set and initial cycle model, they should be able to use this status matching process to mathematically arrive at essentially the same result. While there will always be an element of subjectivity and ambiguity in the status matching process, the method derived from this research should minimize it. Second, the process must account for the various sources of uncertainty in a mathematically rigorous and logical way. These sources of uncertainty are typically due to measurement uncertainties, manufacturing process capability (or lack thereof), and so on. All of this information must be used in the matching process to arrive at matching parameters that have not only a nominal value, but also an uncertainty estimate associated with them. Finally, a probabilistic status matching process should yield some insight as to the confidence intervals associated with predicted engine performance output from the status deck.

It happens that this basic problem is well-suited to analysis using a Bayesian Updating approach. As a simple example, assume we start with a prior belief (based on past experience, for example) of what the distribution of the mean of a matching parameter "X" is and would now like to modify our beliefs of what the true mean of X is based on new test data. Bayesian Updating provides a mechanism for doing this—it can be thought of as an "inverse probability" method. This idea is illustrated in Fig. 1 where we are given an initial set of distributions on model parameters based on current beliefs and past observations of model parameters (the priors). Given a new observation of model parameters (in this example, matching parameters "X1-X4" are measured for several specimens), Bayesian Updating can be used to produce an updated set of distributions that combine the prior beliefs with the new observations. If the input and output distributions can be assumed to be normal, then simple algebraic formulas can be used to calculate the updated mean and variance of the model parameters.[3]

A variation of this "inverse probability" problem is the case where the distribution on X is related to some output parameter, Y=f(X). In this case, instead of being given an updated value of X directly, *we are given an updated value of Y and must use this to infer something about the underlying distributions on X that gave rise to that observed value of Y*. We will refer to this herein as "Inferenceing" as distinguished from "Bayesian Updating" discussed previously. The concept of Inferenceing is shown in Fig. 2. In this case, we already assumed input distributions on the X's (known as *prior distributions*) which have been used to find the output distribution on Y. We are now given an observed value of Y and desire to extract that portion of the input distributions that corresponds to the observed value of Y. That portion of the input distributions are depicted as smaller light-colored distributions inside the original distributions at the right side of Fig. 2, and are known as the *posterior distributions*. The posteriors will generally have a different mean and standard deviation than their prior distributions. The change from the prior is due to the influence of the new observation of Y translated into equivalent distributions on the input parameters. It should be noted that although the posteriors are depicted in Fig. 2 as being smaller than the original prior distributions, the total area under the distribution curve must still be equal to 1.0. Therefore the small distributions actually have the same area as the original distributions. This research is described in further detail in Ref. 4.

PROBABILISTIC ANALYSIS OF LIFE-LIMITED PARTS

Life limited parts (LLP) are those engine parts that have a government- or manufacturer-mandated upper limit on number of operating hours in an engine. In general, LLPs constitute a significant portion of an engine's manufacturing and maintenance cost. Moreover, these parts must be prime-reliable, as failures typically lead to loss of an engine and sometimes lead to life-threatening situations. The former induces one to use the parts as long as possible while the latter demands that parts be replaced more frequently. These

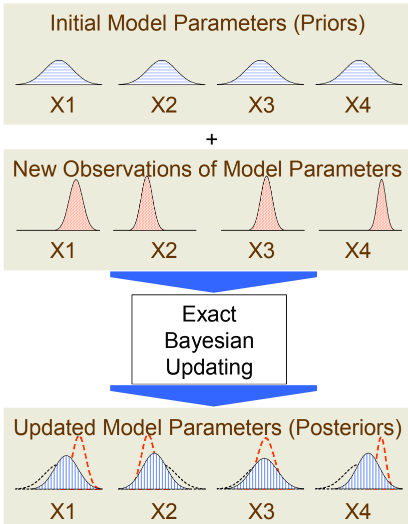

Fig. 1: Bayesian Updating of Model Parameters.

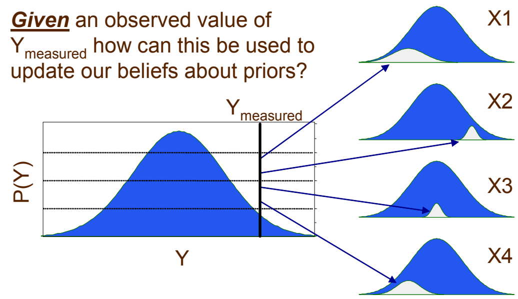

Fig. 2: "Inverse" Probability Through Inference.

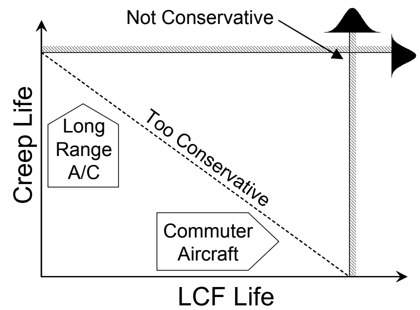

Fig. 3: Competing Failure Mechanisms and Correlation Thereon.

competing requirements are driving current developments in high fidelity analysis methods as well as high-accuracy part inspection methods.

Hot section parts tend to be the most critical of all life limited parts, especially turbine disks, blades, and nozzles. These parts are subjected to a variety of damage mechanisms including creep, low cycle fatigue (LCF), high cycle fatigue (HCF), erosion, corrosion, and oxidation. Damage to these parts is accumulated over time and is a strong function of vehicle mission, operation profile, and other factors beyond the designer's control. In addition, material properties, material cleanliness/flaw size, part loads, and detailed part geometry all play a strong role in determining part life. Therefore, the analysis of part life accounting for all these competing damage mechanisms and their interactions is a challenging problem in itself. However, one must also consider that each of the aforementioned contributing factors has some (non trivial) degree of uncertainty associated with it. For instance, the loads to which the part is subjected may be slightly different than predicted, there may be manufacturing variation in part geometry, the material properties may have deviations from nominal, and there can be flaws in the part that slipped past the inspection process. Thus, the real problem that must be addressed is fundamentally a joint probabilistic failure estimation exercise wherein multiple competing, correlated damage mechanisms must be assessed in the presence of a variety of uncertainties in the problem boundary conditions. As if this weren't difficult enough, one must also remember that the joint probability of failure levels of interest for typical LLP designs is at the very low probability of failure level ($P_{failure}$<0.1%), well into the tails of the distribution where it becomes increasingly difficult to predict probability of failure accurately.

The issue of correlation between competing failure mechanisms is illustrated in Fig. 3. This figure shows two competing failure mechanisms, LCF life and creep life for a given engine part (a turbine blade, for example). LCF life is driven strongly by the number of hot/cold cycles the part experiences while creep is driven by time at high temperature. Translated into operational terms, LCF life is strongly correlated to the number of takeoff and landing cycles while creep life is strongly correlated to total time at a cruise flight condition. Therefore, creep life will tend to be a limiter on part life for long range cruise engines while LCF will tend to be a life limiter for short haul commuter engines. The limits of part life are notionally depicted as hatched lines in Fig. 3. For greatest utilization of these expensive life-limited parts, one should operate the part until all available creep and LCF life has been used up. It should be obvious, however, that creep life and LCF life are not entirely independent. As a result, running the part to the limit of the independently estimated creep and LCF lives (the corner point) is almost certain to lead to more part failures. On the other hand, drawing a straight line between the creep and LCF axes limits is probably too conservative. The

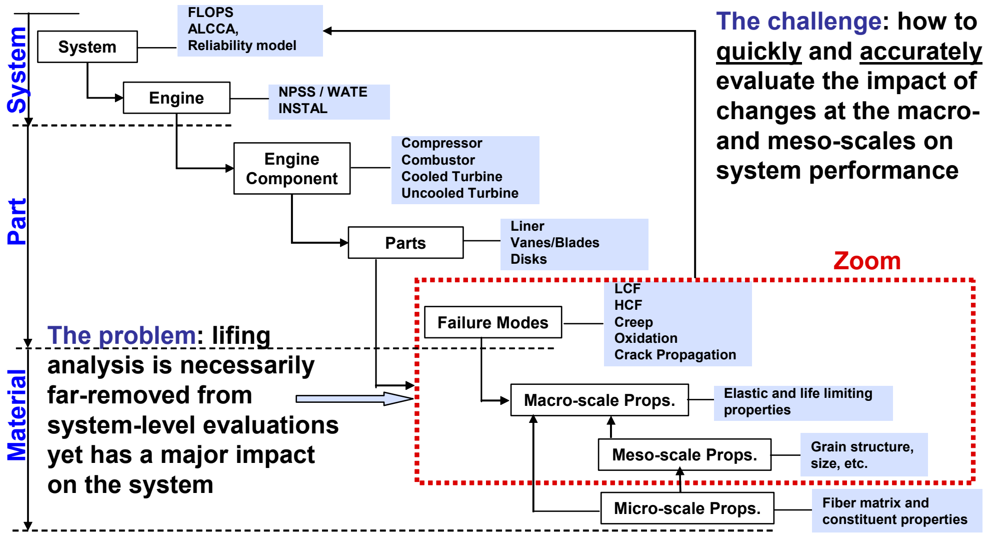

Fig. 4: Bridging the Gap Between Preliminary Engine Design and Materials Design/Part Lifing Viewpoints.

problem therefore becomes one of estimating the joint probability of failure for all the pertinent failure modes. Lest we oversimplify the problem, recall that the various sources of uncertainty in the analysis process dictate that the creep and LCF life limits are not deterministic as suggested by the hatched lines. Rather, those limits must be described probabilistically, as suggested by the probability distributions next to the life limits.

A variety of probabilistic methods have been developed to handle these and other aspects of this complicated part lifeing problem. These methods range from application of simple Taguchi methods[5] to sophisticated methods for system reliability assessment using covariate theory, as described in references 6 and 7. Considerable progress has been made in applying advanced probabilistic methods to evaluation of part life subject to competing loss mechanisms and this is an area of active research at the present time.

Probabilistic part lifeing is intricately related to system performance evaluation as well as the materials technology problem described later in this paper. The relations between these three areas are illustrated in Fig. 4. The status matching problem described previously pertains mainly to the system level, especially to engine performance. Probabilistic part lifeing is intricately linked to detailed part geometry/loads, materials microstructural properties, and analysis of failure modes (labeled “part” level in Fig. 4). It therefore lies at an intermediate level of analysis detail. The engine material technology problem described in the following section is principally concerned with very fine-scale materials microstructure and properties (“material” level in Fig. 4). However, the impact of materials technology propagates upward through the various levels of analysis fidelity and is ultimately felt at the very top levels of system performance. This is a key quandary: materials microstructure and part failure modes depend on very fine-scale details and is therefore far-removed from system-level analysis, yet their impact is felt at the highest levels of system performance. As such fine-scale details can never be ascertained at the system level, the only viable alternative is to quantify the impact of each level on the next highest level in terms of some gross (that is, probabilistic) terms that can be incorporated in the next highest level without undue complexity. It follows that a *global* probabilistic formulation is therefore imperative.

ENGINE MATERIALS TECHNOLOGY UNCERTAINTY

Materials technology has long played a pivotal role in defining propulsion technology and capabilities. In fact, materials technology largely sets the pace of advance in propulsion technology. It is therefore of obvious importance to foster continued advances in the area of materials technology with the greatest possible efficacy.

The materials development process is by its nature time-consuming. The time needed to design and test a new material to the point where there is sufficient confidence to use it in flight-worthy hardware can take a decade to complete. The engine development cycle, by contrast, is usually less than this, and efforts are underway in all three major engine companies to reduce engine development time to two years from program launch to certification. Inasmuch as the materials properties are driven by the needs of engine designers, continued advances in propulsion technology are in some measure dependent on the ability of the materials community to develop new materials to meet future engine needs. Obviously, a large mismatch between the materials development time and the engine development time is not conducive to continued rapid advance of engine technology.

This growing incongruence in development times has led to efforts in the materials community to shorten the time required to bring a new material to market. Current programs are focusing on to shortening materials development time principally through improved computational materials/processing models. This will in turn enable the "virtual testing" of many more materials concepts than was previously possible through physical testing. A second part of current efforts is creation of "design knowledge base" expert systems. Such tools are intended to facilitate the use of the most current materials and processes available during the design of critical engine components. These efforts will also increase the efficiency with which the materials design space can be characterized and "sweet spots" identified.

Another approach to help avoid the mismatch of materials and engine development times is to find methods that assist materials engineers in better anticipating future materials requirements. This effectively lengthens the lead time available for materials development. Any means that will assist the materials community to more precisely identify the exact combination of properties that would be best suited for an imminent engine component requirement would contribute to the goal of promoting materials technology. This approach has received less emphasis than reducing materials development time, but is a logical means to help solve the problem.

Finally, the development of new materials computational models will enable the exploration of many more materials systems than was previously possible. As such, new methods for systematically organizing and searching these new materials domains will be required. Some means for addressing this sorting problem must be developed if we are going to fully utilize the new capabilities being developed in computational materials.

Given this present state of research activity, the three key research areas where we are attempting to make a contribution to the state-of-the-art are: 1) characterization of materials requirements, 2) development of robust materials, and 3) insertion of materials technology. To understand these research areas and their relationship to one another, let us briefly consider the nature of materials technology. In particular, materials technology is characterized almost entirely in terms of material properties. Each of these properties is unique and embodies a particular aspect of material performance. Thus, we can view materials properties as a multi-dimensional space, with each property lying on an axis of this space. If all classes of materials are cataloged and plotted as points in this multi-dimensional "properties space," one finds that the collection of all materials forms a Pareto front that effectively defines the materials technology state-of-the-art. This is essentially the view of materials properties suggested by Ashby,[8] as shown in Fig. 5. Although Ashby presents materials properties in terms of combinations of properties, the concept is still the same: *every material maps to a point or region in the material properties space*. Note that Ashby's plot shows a very wide diversity of material types plotted in two dimensions of the "properties space." Every known material can be plotted on this chart if so desired.

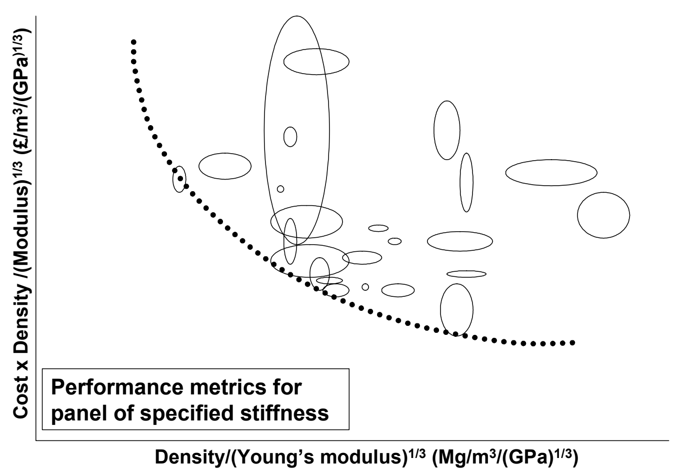

Fig. 5: Ashby Plot of Materials Technology Pareto Front (After Ashby).

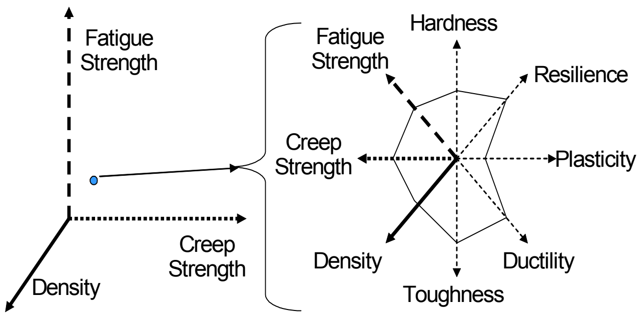

Fig. 6: Mapping Materials Property Space to "Radargrams."

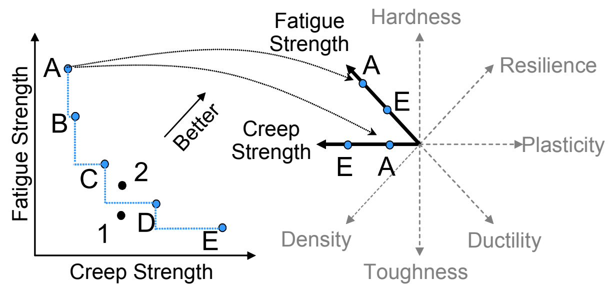

Fig. 7: Pareto Frontier, Non-Dominated Points, and Their Relation to Spider Charts.

A feature of particular interest on this plot is the locus of points that define the bounds of the known materials space. It is clear from this plot that there is an inherent tradeoff between the two materials properties—an improvement in one axis leads to a degradation of the other. This tradeoff surface (also called a Pareto front) effectively *defines the state-of-the-art material capability* with respect to these two properties. Although this plot shows a two-dimensional cross-section of the Pareto frontier, one can readily imagine that the true frontier is an n-dimensional space, where n is the number of materials properties needed to characterize any material.

If it were somehow possible to plot each of these properties on the axis of an n-dimensional "material properties space," the result would be a Pareto frontier of materials properties that *completely characterizes the state-of-the-art in materials capability*. Thus, the crux of *materials technology* is finding means for advancing the known frontier of materials properties. The crux of *materials planning* is figuring out in what direction we should push the advance of that Pareto frontier so as to meet future needs. *Materials design* is the process of creating materials that lie at a given point on the properties frontier. *Materials selection* is about finding what point on the Pareto frontier best fits a particular application. An *optimal material* for a given application can be defined as a material lying on this n-dimensional Pareto frontier and having the combination of materials properties that is optimal for the application. In short, virtually everything important about materials can be explained in terms of this material properties Pareto frontier.

Unfortunately, it is difficult to visualize spaces of more than 3 dimensions. In most cases, we will be interested in more than three material properties for a particular application, so alternate representations are needed that will allow consideration of more material properties simultaneously. One such representation is given in Fig. 6. Consider three dimensions of an n-dimensional space, notionally shown on the left side of Fig. 6. Every material maps to a point or region in this space. One way to visualize the same information is to plot the property set of each material in the form of a "spidergram" or "radargram." Every point in the n-dimensional property space maps to a particular radargram, as shown at right in Fig. 6.

Any material that lies on the materials Pareto front must have a radargram which is non-dominated by any other material radargram. That is to say that a material which lies on the materials Pareto front will have a radargram that is better than every other known material in at least one leg. To understand the concept of domination and Pareto points, consider Fig. 7. The left side of this figure shows a simple two-dimensional Pareto front. This front is defined by a collection of non-dominated points, a-b-c-d-e. A point is said to be non-dominated if it is better than every other point in *at least one* property axis. Thus, if up and right is "better", then point 2 is on the Pareto front because it is better than every other point in at least one dimension. Conversely, point 1 is not on the Pareto front because it is dominated by point D. Each point on the Pareto front readily translates into an equivalent radargram representation. If a material is on the Pareto front, then it's radargram will be better than every other material in *at least one leg*. Conversely, a material does not lie on the Pareto front if there is any material that betters it *on every leg*.

This "radargram" representation of materials properties enables us to classify materials in a few intuitive categories. For instance, specialty materials will be the ones which generally exhibit a very long leg in one axis, at the expense of another axis. Turbine blade and disk materials are examples of specialty materials that have evolved into increasingly narrow niches with each passing generation of materials technology. The "robust" material,† on the other hand, will not exhibit spectacular performance on any one axis, but will exhibit

† "Robust" in this sense is taken to mean a material that has well-balanced properties and is therefore a reasonable candidate for a wide variety of applications, though it may not be optimal for any particular application.

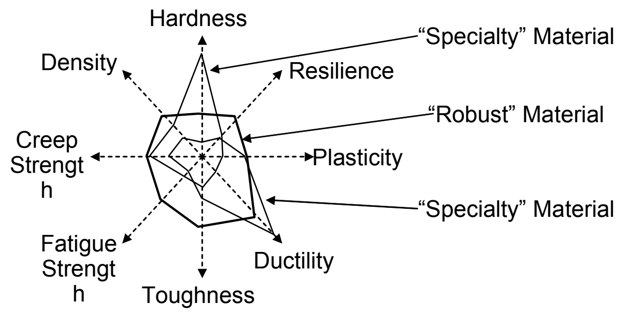

Fig. 8: Materials "Robustness" as Measured Using a Radargram.

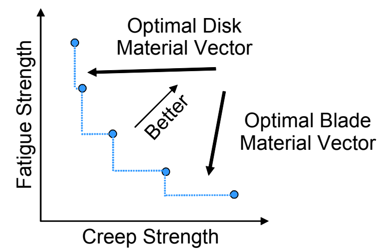

Fig. 9: Material "Requirements Vector" for Various Blade and Disk Applications.

good performance on all axes such that it is better than all "specialty" materials in at least one axis. The widespread and varied use of Inconel 718 in engines suggests that it is somehow a "robust" material. This idea is illustrated in Fig. 8 for three hypothetical materials. Two radargrams represent "specialty" materials that are thoroughbreds in a single category and are generally characterized by lop-sided radargram plots. The robust material exhibits relatively good all-around performance and is marked by a relatively symmetric radargram.

Continuing along this path of thought, one can readily surmise a few questions that are of prime importance for materials technology research. One of these is the "material requirements" problem: how does one identify the "material requirements vector" associated with a particular material application? For instance, how does one determine what combination of properties is optimal in a turbine disk or blade material? Returning to the two-dimensional Pareto front of Fig. 7, it is intuitively obvious that creep strength is more important for turbine blade materials while fatigue strength is more important for disks. Each application is therefore manifested as a unique "requirements vector," as shown in Fig. 9. If the material property importance weightings for a particular application can be identified, it would be useful in developing next-generation materials for that application. Further, if all existing materials for that application were plotted superimposed on a single radargram, the properties having relative weakness or improper proportions will be readily apparent. This will then provide some guidance relative to what combinations of materials properties need further research and development.

Returning to Fig. 5, note the "gaps" in the tradeoff space where materials science has not yet produced a material capable of meeting the requirements. Even though a particular combination of materials properties may seem to be within the current materials technology Pareto frontier, materials science may not have yet produced a material that has that particular combination of properties. This leads to another interesting materials research question: what uses would such a "gap filler" material might be good for if it were to be developed? Are there places where there are "gaps" in the present materials that could potentially be "filled in" through new materials tailored to fit in those gaps? The corollary to this question is: what points along the Pareto frontier is there the greatest need for materials improvement? I.e. what directions should the Pareto frontier be pushed even further out in order to yield the greatest benefit? These two questions constitute the "material technology insertion" problem mentioned in the introductory paragraph of this section.

COMPONENT-CENTRIC VERSUS MATERIALS-CENTRIC APPROACHES

The technology frontier concept provides a simple and intuitive view of materials technology. However, it is somewhat abstract, so it is perhaps worthwhile to couch these concepts in terms that are more familiar to materials developers. Consider that there are two basic avenues of approach to defining future materials technology. One approach is to take a component-centric view wherein those engine components offering the most challenging materials requirements are identified for special attention. These critical components are then analyzed, particularly with regards to design trends over time. If one can ascertain what materials properties will affect the greatest possible engine benefit (in terms of weight, performance, reliability, or cost), one can undertake the tailored design of materials created specifically for maximum performance based on these projections. Ideally, one would like to examine what the top-level requirements for next generation vehicles will likely be, translate these into engine requirements, and ultimately into component and materials requirements. This approach is usually characterized as "materials planning" and "materials design."

The alternative approach is to take a materials-centric point of view wherein new materials are examined with the objective of producing materials that are superior to the best materials currently available in at least

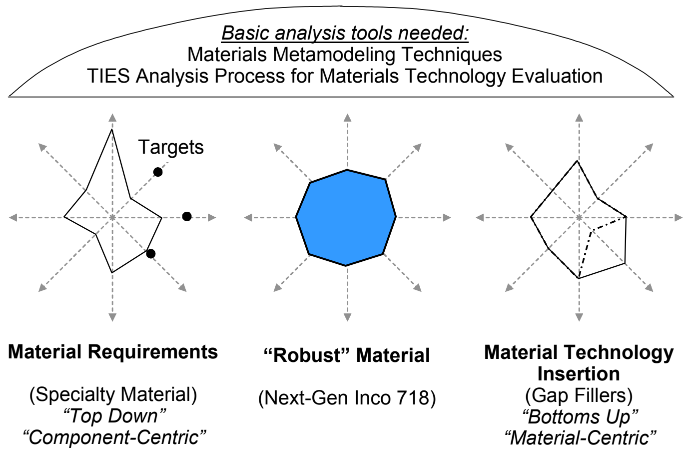

Fig. 10: Broad Classes of Materials Research Challenges and Common Research Elements Required to Address the Three Basic Challenges.

one aspect. Having identified a new material with at least one outstanding property, one can undertake a systematic examination of where such a material could be put to greatest use. In the limit, one would like to carry this material benefit through to its impact on flowpath, engine performance/weight, and ultimately impact on the entire vehicle. Evaluating material impact at the system level (as well as evaluation system level requirements impact on materials needs) is not a trivial task and will be a key area where ongoing research in the area of advanced/probabilistic design methods can assist the materials community.

ROBUST MATERIALS

One of our main interests in materials technology research is to better understand what constitutes "robustness" in a turbine engine alloy and develop methods to assist in the development of next-generation "robust" materials. Robustness in this context means flexibility to be used in a wide variety of applications. Since the production cost associated with a given material is strongly related to the volume of production, it is imperative to focus on developing materials that will have the broadest possible range of applications, not only because volume production reduces material cost, but also because it saves R&D cost of needing to develop a new material and also has "brand name" value relative to designer familiarity and comfort level with a commonly-used material for which the limits are well-known.

One possible approach to address these questions is to use Technology Identification, Evaluation, and Selection (TIES) methods as a means for identifying materials needs. The basic TIES method as described in Ref. 9 is well-suited to this type of problem. The robust material problem will also likely require the application of the feasibility/viability evaluation methods described in the following section. Several additional modifications will be required to address needs peculiar to materials technology evaluation. In particular, innovative materials modeling or metamodeling methods are necessary to enable expedient examination of the materials design and requirements spaces.

These three main materials research challenges are summarized in Fig. 10 along with the basic analysis methods that will be needed to solve all three problems. The component centric approach can be thought of as a "top down," "requirements-driven" method while the materials-centric approach can be thought of as a "bottoms up," "gap-filler" method. Both can be addressed through judicious application of TIES techniques, as described later in this proposal. The solution of all three research problems depend on the development of advanced TIES and materials metamodeling techniques to enable timely solution of the problem.

FEASIBILITY AND VIABILITY ASSESSMENT

The first step in developing a new material to meet a set of prescribed goals should be to establish the feasibility and viability of meeting the goals. If the materials requirements are met by an existing material, then there is no need for further effort on the part of the materials designer. If the goals are within the Pareto frontier of current materials technology but there is no currently available material capable of meeting the requirements, then it may be that parameter settings of current materials can be adjusted to produce a new variation of material that fits into the gap. If the goals are clearly in excess of what can be achieved using current material technology (i.e., beyond the Pareto front), then it is necessary to consider applying new technologies that may enable materials capable of meeting the goals.

Various authors have been working over the past five years to develop general methods to assist designers in determining feasibility and viability through probabilistic means.[10] Though these methods have hitherto only been applied to aircraft and engine systems, they are just as applicable to engine materials development. Our present work seeks to leverage existing feasibility/viability and TIES methods towards application to the engine materials development and selection process. It is therefore useful to give the reader a brief overview of probabilistic feasibility/viability as it pertains to engine materials.

At any given time in a materials development program, there are always a variety of options available for implementation, each having a different readiness level, with unique risks as to how it will perform outside of a laboratory environment. What is needed is a systematic, analytical environment for feasibility assessment and selection of technology options. This environment must be capable of accounting for interactions, technology readiness and risk, and must enable the designer to quickly and easily investigate the merit of various materials technology options.

To understand the methods proposed to solve this technology problem, it is necessary to start with the underlying probabilistic concepts that are the foundation of this technique. In probabilistic design, the outcome sought is either a cumulative distribution function (CDF) or a probability density function (PDF) for each design objective or constraint. These distributions represent the outcomes of every possible combination of synthesized designs so it is a representation of the feasible design space against which the decision maker can now compare a desired target value. Based on these results, decisions concerning relaxation of targets, relaxation of constraints or infusion of new technologies can be made. The generation of these distributions entails the linking of complex computer codes with statistical techniques. This procedure is accomplished by the use of the Fast Probability Integration (FPI) software package that links the sophisticated analysis code with an approximation of the Monte Carlo Simulation.

The probabilistic technique described above will then be applied to the intermediate steps required in this process to determine system feasibility and viability. Technical feasibility in this case is a measure of the system’s ability to meet performance goals and satisfy imposed performance constraints. Technical feasibility is assessed by changing control variables only and generating CDFs for each performance objective/constraint. Economic viability, on the other hand, is a measure of the system's ability to achieve affordability goals and satisfy imposed economic constraints. Economic viability is assessed by varying control and noise variables and generating cumulative distribution functions for economic objectives/constraints. Technical feasibility must be established before economic viability is assessed. The steps required to determine if feasible and viable design space exists and open these design spaces, if necessary, is presented in Fig. 11. The steps in this methodology are: problem definition, system feasibility determination, feasible space examination, new technology infusion, and robust design simulation.

Once the CDFs are constructed the designer can overlay the constraint values and immediately determine the active constraints, thus making the percentage of the design space satisfying each constraint evident. Once this identification is made, there are two avenues available to “open the feasible space”: 1) relax the active constraints and/or 2) infuse new technologies. In the case of the latter option, the power of the Fast Probability Integration technique is exploited since this technique not only constructs the CDFs but also provides probabilistic sensitivity derivatives. These sensitivity derivatives provide insight into the most important variables for each constraint and a starting point for the decision-maker in choosing a new technology aimed at a specific constraint.

If gains towards meeting materials goals through optimization of design parameters does not yield further progress and the goals have been relaxed as far as is allowable, then the only other option left is infusion of a new technology. The maximum level of a given technology is essentially the natural limit of the benefit, displayed in Fig. 12. This implies that the maturation variation with time remains constant. When this limit is reached, there is *no other alternative* but to infuse a new technology. The result in Fig. 13 would be typical of the results for the objective or constraint at which the new technology is directed. *However, new technologies cannot be assessed from a benefit viewpoint alone. The effect on other disciplinary metrics must be included to see how the new technology penalizes the various objectives and constraints and how it affects the design space.*

This method can quickly and easily assess the impact of advanced materials technologies *including* interactions between technologies and other systems. This approach also expedites the technology

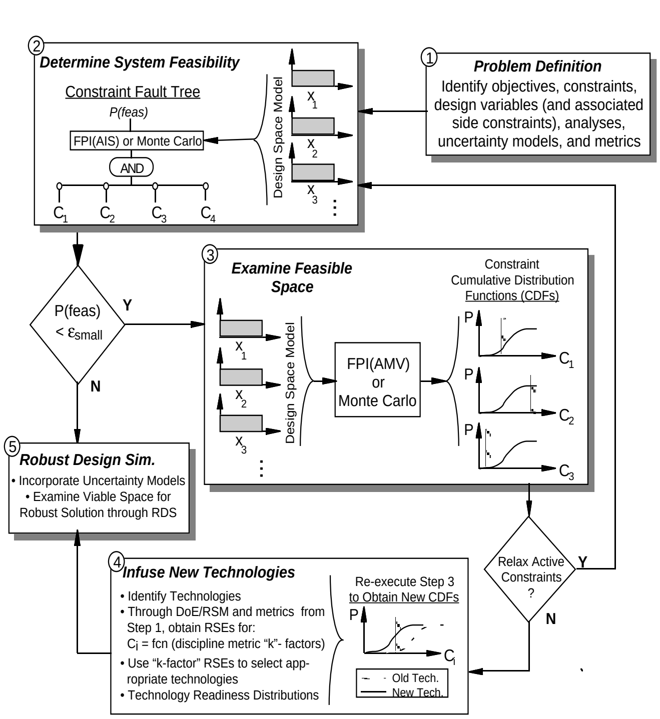

Fig. 11: Feasibility & Viability Determination [Ref. 11]

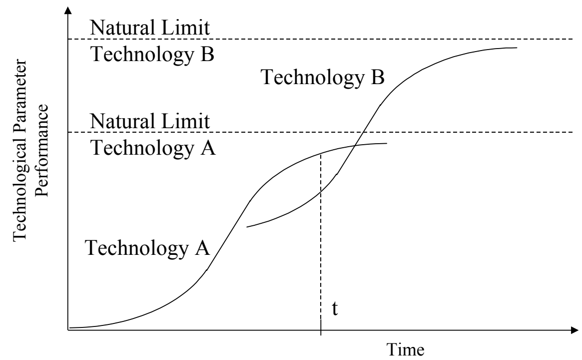

Fig. 12: Infusion of New Technology

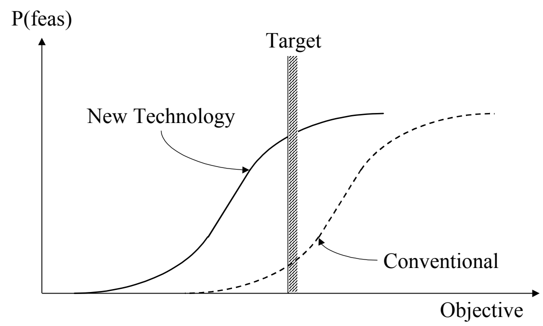

Fig. 13: New Technology Improvement

evaluation because the TIES method described earlier provides a means of quickly and accurately investigating technology "what if" scenarios without the need to re-run a new analysis case for each scenario.

SUMMARY AND CONCLUSIONS

Each of the three research efforts mentioned herein is inherently linked to probabilistic analysis methods in that uncertainty plays a key role in defining all three research problems. The methods presented here are still work in progress, but all show considerable promise as means to address each of the problems presented. There is no doubt that there is a great deal of work remaining to bring the research areas described in this paper to a state of relative maturity. This work is being carried forth by the present authors as well as many others and promises to be an exciting and challenging area for research for years to come.

ACKNOWLEDGMENTS

We would like to thank Dr. Vitali Volovoi and Mr. Jon Wallace for their contributions to elements of this paper. We would also like to thank our sponsors for their contributions to the various research projects described herein. In particular, we would like to thank the Office of Naval Research Affordability Program (grant N00014-97-1-0783), NASA Glenn RC for providing assistance under the URETI program, GE Aircraft Engines under the University Strategic Alliance (USA) program, and GE Power Systems.

REFERENCES

1. Roth, B. Mavris, D., "Commercial Engine Architecture Selection in the Presence of Uncertainty and Evolving Requirements," AIAA Pub., ISABE2001-1169.

2 Roth, B., Doel, D., Mavris, D., and Beeson, D., "High-Accuracy Matching of Engine Performance Models to Test Data," ASME Turbo Expo, GT2003-38784.

3. Gelman, A., Carlin, J., Stern, H., Rubin, D., ***Bayesian Data Analysis***, Chapman & Hall, Boca Raton (1995).

4 Roth, B., Mavris, D., "Estimation of Turbofan Engine Perofrmance Model Accuracy and Confidence Bounds," AIAA Pub., ISABE2003-1208.

5 Wallace, J., Wojcik, S., Mavris, D., "Robust Design Analysis of a Gas Turbine Component," ASME Turbo Expo, GT2003-38546.

6. Wallace, J., Mavris, "Simulation-Based Parametric Reliability Modeling Using Covariate Theory," ASME Int'l Eng. Congress, IMECE2003-43945.

7. Wallace, J., Mavris, D., "Creep Life Uncertainty Assessment of a Gas Turbine Airfoil," AIAA2003-14841.

8. Ashby, M.F. "Multi-objective optimization in material design and selection" ***Acta Materialia***, v 48, n 1, (Jan, 2000).

9. Roth, B.A., German, B.J., Mavris, D.N., "Adaptive Selection of Engine Technology Solution Sets from a Large Combinatorial Space," AIAA2001-3208.

10 Mavris, D.N., DeLaurentis, D.A., "A Stochastic Design Approach for Aircraft Affordability," 21st Congress of the International Council on the Aeronautical Sciences (ICAS), Melbourne, Australia (September 1998).

11. Mavris, D.N., DeLaurentis,D.A., Bandte,O., et al., "A Stochastic Approach to Multi-disciplinary Aircraft Analysis and Design", Presented at the 36th Aerospace Sciences Meeting & Exhibition, Reno, NV, (January 1998).